gaia-x

Hub Germany

# AI and Gaia-X

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## About the series

White Papers of the Gaia-X Hub Germany are intended for discourse and the exchange of ideas. They reflect the opinions of the authors and not necessarily those of the Gaia-X Association or any other institution of the Gaia-X ecosystem.

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# Summary

Artificial Intelligence (AI) is not a new topic and Gaia-X has been involved with AI from the very beginning. Not only does the Gaia-X ecosystem enable the development and use of AI by addressing many of the challenges that AI faces, but there are also a number of Gaia-X projects that deal with AI to varying degrees.

However, even if we hear about individual projects or initiatives, there is no clear, systematic overview of AI in the Gaia-X context. This paper provides that overview. It should be noted that this paper does not address every feature and issue related to AI and Gaia-X, nor every AI-related project within Gaia-X. Rather, it seeks to provide clarity and enable those less familiar with Gaia-X to gain a solid understanding of AI in the Gaia-X context.

**The first part** of the paper provides an overview of AI and highlights the complexity and multi-layered nature of the topic. This is followed by an overview of some of the key challenges facing AI. In order to provide a more systematic and clearer overview, these challenges are divided into the following sections: economics/organisation, technology and regulation.

**The second part** of the paper outlines the global competitive landscape in the field of AI and outlines the EU and German government's AI strategy. Here, the significance of Gaia-X for AI is contextualised, in particular the importance of data spaces for the development of AI in Europe.

**The third part** introduces Gaia-X and explains how it can enable the development of AI by addressing many of the challenges described in the first part.

**Part four** then deals with three AI-related Gaia-X projects. EuProGigant (Industry 4.0) and Gaia-X 4 AI (Mobility) were selected due to the importance of these sectors for the German economy. OpenGPT-X (large language models) was selected because of the role that large language models have played in the re-emergence of AI as a very current topic.

# 1. Artificial Intelligence

## 1.1. Overview

Artificial intelligence (AI) is already permeating our everyday lives. It protects our email inboxes from spam, organises our search results and recommends products when we shop online. What AI is and what it does, however, is unclear to many users. One of the reasons for this is that AI is characterised by a high degree of complexity and offers countless possible applications. The definition of AI is correspondingly difficult. Artificial intelligence is often defined in contrast to human intelligence. For example, a distinction is made between ‘weak/narrow’ AI, systems that can solve specific questions or problems (e.g., Siri and Alexa), ‘strong/general’ AI, which can solve general problems just as well as humans, and ‘superintelligence’, AI systems that significantly exceed human performance (although there are currently no real cases for the last two categories). Overall, there is no consensus on the definition of AI, but for the purposes of this paper, we will refer to the definition from the *Plattform Lernende Systeme (PLS)* glossary: "AI is a branch of computer science that attempts to realise cognitive abilities such as learning, planning or problem solving in computer systems with the help of algorithms (PLS Glossary)".

Further complexity arises from the fact that there are various approaches and methods for developing AI. One of the most important of these approaches is Machine Learning (ML). Machine learning refers to the "[...] training of computers to learn from data and experience and constantly improve - instead of being explicitly programmed to do so (SAP)". ML itself can be divided into three main categories: Supervised ML, Unsupervised ML and Reinforcement ML. According to Kirste and Schürholz (2019), in supervised learning "a computer program receives known data examples and is trained for a desired interpretation and the associated output. The aim is to find general rules that connect the known input data with the desired output data and then use these rules to create new outputs with new input data (Kirste and Schürholz 2019, p. 25)".

Unsupervised learning "works without previously known assignment and labelling of input data. The possible results are completely open. Therefore, the computer program cannot be trained, but rather has to recognise structures in the data and transform them into interpretable information (ibid. p.26)". In reinforced learning, "a computer programme learns directly from experience. To do this, it interacts with its environment and receives a reward for correct results (ibid. p.29)".

One particular keyword that has gained a lot of traction recently and is a subset of machine learning is 'deep learning', which utilises so-called ‘Artificial Neural Networks (ANNs)’. Deep learning and machine learning as a whole are at the centre of the resurgence of AI. AI is indeed not a new development and has gone through various ups and downs since the 1950s. However, advances in computing power, the exponential increase in the amount of data available and new algorithms have enabled AI to reach new heights. It is important to emphasise that

AI systems not only require an enormous amount of data, but that the data must also be of sufficiently good quality.

## 1.2. Pros and cons

The latest advances with AI have led to the benefits, particularly the economic benefits, becoming more apparent. According to PwC (2017), for example, global GDP could increase by up to 14% in 2030 as a result of the use of AI. PwC predicts that the increase in GDP due to AI by 2030 will be 26.1% in China, 14.5% in North America, 9.9% in Northern Europe and 11.5% in Southern Europe. These figures illustrate the regional differences when it comes to the potential economic impact of AI. Economic gains will most likely come in the form of productivity gains through the automation of certain business processes and assisting the labour force. In addition, the use of AI technologies will provide new insights from data that will open up business opportunities and enable companies to offer relevant services and products to their customers (see for example, Szczepański 2019). Another advocated benefit of AI is, for example, its contribution to science. Stanford's Artifical Intelligence Index Report 2023 by Maslej et al. (2023) outlines how AI has contributed to scientific progress: in 2022, for example, AI was used to improve the efficiency of matrix manipulation, develop new antibodies and support nuclear fusion.

In addition to the many advantages that AI offers, it also harbours considerable risks and challenges. These include, especially in the case of machine learning and deep learning, the 'black box' problem of algorithms. According to PLS (2019), the black box phenomenon refers to the fact that it is "almost impossible for users to understand what happens inside the system and how the algorithm arrives at its behaviour (PLS 2019, p.49)". Why an algorithm arrives at a certain solution is therefore opaque and thus a 'black box'. This is particularly problematic when you consider that AI has been shown to discriminates against certain groups and is often biased (see Borgesius 2018). This is the result, for example, of biases that are often contained in the data on which the algorithms have been trained and which they replicate. Another major problem is that AI can also be used for dubious purposes, for example for mass surveillance, to weaken democratic institutions or to manipulate people. The tools used include bots, disinformation and deep fakes.

There are also concerns about its impact on society and humanity. These include specific fears about AI taking over jobs and its impact on the labour market, as well as broader societal concerns. In fact, many prominent figures, including from the AI world (such as Sam Altman, CEO of OpenAI), have signed the *Centre for AI Safety Declaration of AI Risks* as follows: "Mitigating the risk of extinction from AI should be a global priority alongside other societal-scale risks such as pandemics and nuclear war (CAIS)". More transparency, traceability and explainability of AI algorithms and the data on which they are based are essential to mitigate the negative effects.

## 1.3. Challenges

The challenges in the development of AI systems and those faced by companies in general when using AI (see Rammert 2021) are diverse and can vary depending on the area of application. Nevertheless, there are certain challenges that dominate and are divided here into the categories of economics/organisation, technology and law (some have overlapping characteristics).

### 1.3.1 Economics / Organisation

#### Trust

AI is confronted with several challenges. First of all, it is important to significantly increase the transparency, traceability and explainability of AI algorithms and the data used in order to create trust in AI systems. For no matter how ground-breaking a technology may be, without public trust and acceptance it runs the risk of not being able to prevail. In fact, an IPSOS survey from 2022 found that while 78% of respondents in China agreed with the statement that products and services that use AI have more benefits than drawbacks, only 35% of respondents in the US said the same (IPSOS 2022). This is all the more remarkable given that the US has been at the forefront of recent AI advancements. In Germany, with only 37% of respondents agreeing, the percentage is also quite low. Therefore, public trust and acceptance of AI cannot be taken for granted. Overall, trust in AI systems is essential if the economic potential of AI is to be fully realised.

#### Access to high-quality data

Trust also plays an important role when it comes to gaining access to a sufficient amount of high-quality data. This is because companies often fear losing control of their data, that their trade secrets will leak out and that the data could be used against them by their competitors (see Pawelke 2020). Confidence that their interests will be protected in this regard is therefore essential if companies are to provide access to their data - especially large amounts of data or very valuable data.

#### Marketplace: consumers and providers

As with all new products and services, those who offer AI products and services must be brought together with those who use them. The first step, of course, is to build trust in the AI systems themselves so that consumers will use the AI products and services. In addition, many companies that develop AI products and services do not necessarily have an existing customer list and contacts to fall back on as soon as they are founded. Even if a product or service would appeal to many consumers, a company's entire business model could be jeopardised if consumers are unaware of it. The key word here is market visibility.

#### Lack of qualified specialists

In order not only to develop AI systems, but also to interact with them and use them effectively, you need the necessary skilled labour. However, there is a general shortage of workers with sufficient IT skills, not just in the field of AI. A study by Regina et al. (2023) shows that the number of vacancies in the IT sector in 2022 was almost 68,000. A Bitkom study (2022) shows that looking at the entire economy and across all sectors, there were 137,000 IT jobs to be filled in Germany in 2022, more than ever before. This is particularly problematic in the context of AI, as the most effective development of AI depends on a wide range of IT-related skills. For example, more IT professionals across the economy to ensure that the data collected is properly formatted and cleansed will help to expand and optimise its effective use for training AI systems.

### 1.3.2 Technology

#### Interoperable infrastructure

Most IT infrastructures today are not interoperable. However, in order to use AI efficiently, an interoperable infrastructure is required. This enables the transferability of AI processes to other data sources and the reuse of algorithms and data through standardised formatting of data and data models (see Seifert et al. 2018, p.29). In addition, the lack of an interoperable infrastructure leads to a less effective and efficient AI system, regardless of whether it is supplying AI systems with sensor data or processing data at the edge.

#### Data quality

One of the biggest challenges for AI systems is gaining access to high-quality data for training. High-quality data is so important because the quality of the data has a direct impact on the reliability, accuracy and performance of AI models. A term often used to describe this problem in the context of data and AI models is 'Garbage In Garbage Out (GIGO)' (Ataman 2023, Grodon-Morrison 2022). High-quality data leads to more reliable and accurate models, which in turn affects how trustworthy the models themselves are perceived to be (Ataman 2023). The quality of the data depends on a variety of factors, including completeness, consistency, accuracy, timeliness, relevance and uniqueness (Ataman 2023, Grodon-Morrison 2022, Budach et al. 2022).

#### High Performance Computing (HPC)

HPC is of central importance for the training of AI models. This is related to the complexity of the AI models, the training time, the size of the data sets, the memory requirements and other factors. For example, AI models, especially large language models, are becoming increasingly complex and have many parameters that require powerful computing power. In addition, many mathematical calculations are performed on huge data sets, all of which require enormous computing power. Many of the high-performance computers are located in the USA, where most AI models are also developed. This leads to a dependency on US AI models that may not reflect European characteristics and interests, limiting Europe's digital sovereignty (KI Bundesverband, 2023). Although Germany has some high-performance computers, the infrastructure is not considered sufficient by the *KI Bundesverband (2023)*.

### 1.3.3 Regulation

#### AI Act

A major challenge is compliance with the EU regulations and the resulting legal uncertainty. The piece of legislation with the most direct relevance is the proposed EU AI Act. It aims to strengthen the rules on data quality, human oversight, transparency and accountability (WEF 2023). At its centre is a classification system (unacceptable risk, high risk, limited risk, minimal/or no risk) that determines how harmful an AI system can be to a person's fundamental rights or safety (ibid.). For example, while systems categorised as limited risk are only subject to transparency obligations, systems categorised as unacceptably risky are not permitted (EC 2023). In the case of AI systems categorised as 'high risk', there are requirements for high data quality, documentation and traceability, transparency, human oversight, precision and robustness (draft AI Act, COM (2021) 206 final).

#### General Data Protection Regulation (GDPR)

The General Data Protection Regulation (GDPR) also has a significant impact on AI and its development. The aim of the GDPR is to protect personal data and give consumers more control over its use. This is intended to strengthen consumer confidence in the digital economy. Ultimately, the GDPR consists of various provisions that determine how much data, especially data containing personal information, may be collected and processed. This naturally has an impact on AI, which is dependent on data. The GDPR contains a number of relevant provisions, such as data minimisation, purpose limitation and the requirement for the data subjects' consent (EPRS 2020). Another relevant GDPR provision with regard to AI is automated decision-making (Art. 22, GDPR).

## 1.4. Application areas of AI

The extent to which AI is used varies depends on the sector or application area. Recently, for example, the success of OpenAI's ChatGPT has led to a rush of investment in large language models. These large language models fall into the area of General Purpose AI, which offers applications that can be useful for a variety of sectors. The area that is receiving the most investment globally is 'medical and healthcare', followed by 'data management, processing and cloud' and 'fintech' (see Fig. 1).

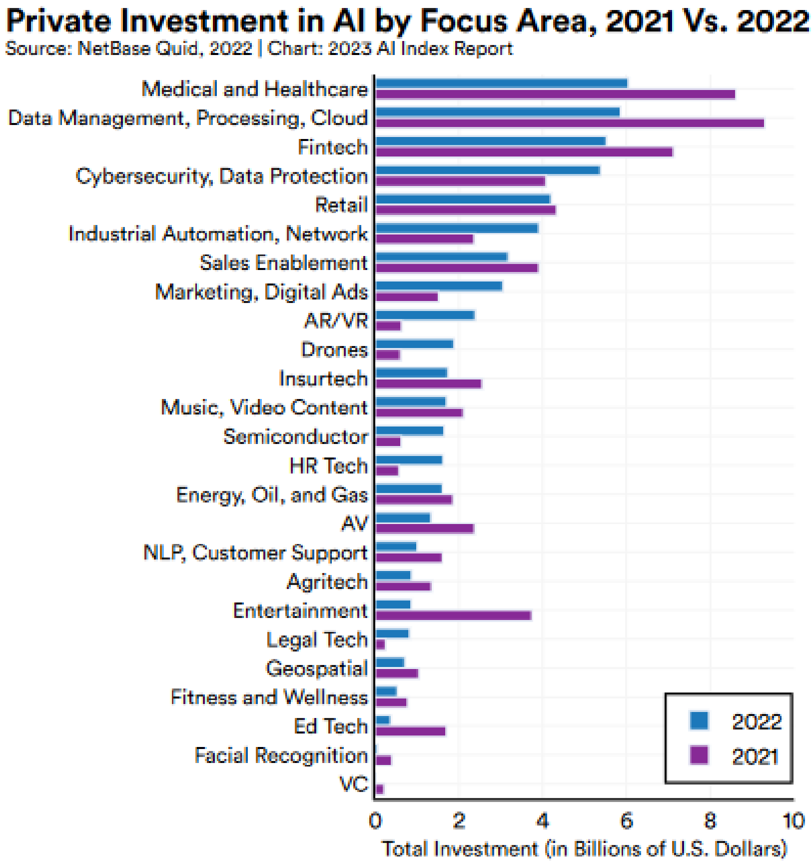


*Figure 1: Private Investment in AI by focus Area, 2021 vs. 2022 (source: Maslej et al. 2023)*

Although there are often many parallels when it comes to which sectors receive the most investment, there are still differences between countries. These depend on whether governments are pursuing a specific AI strategy and which industries and sectors are most strongly represented in the economy of the respective country. The PLS (2019), for example, has created an AI map for Germany that shows the various AI applications by sector (see Fig. 2).

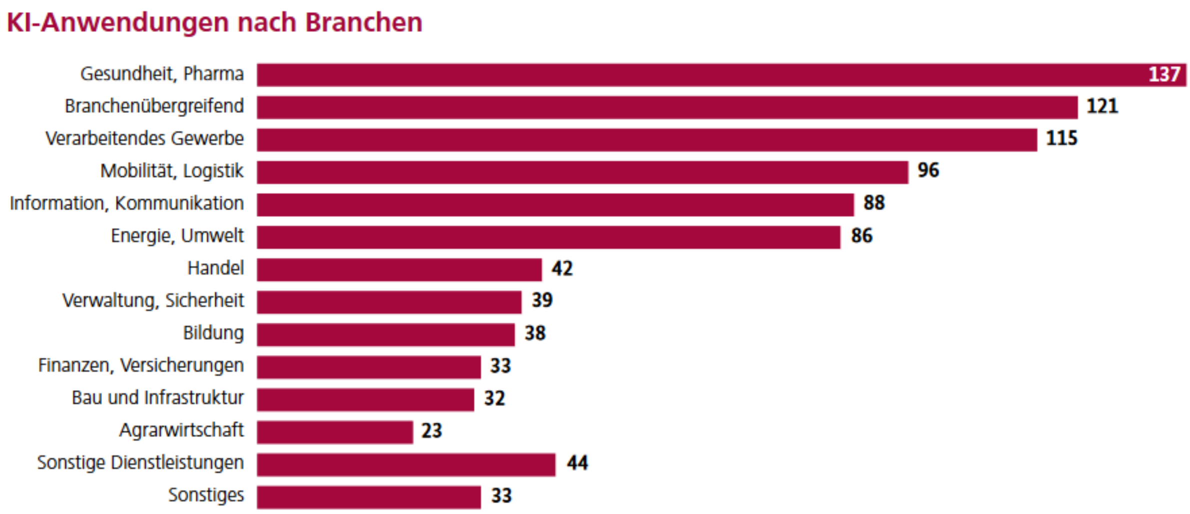


*Figure 2: AI applications by sector (source: Plattform Lernende Systemen 2019)*

Although the healthcare sector is still in the lead, it quickly becomes clear that the 'manufacturing industry' and the 'mobility sector', for example, play a greater role in Germany. This is also reflected in the number of AI start-ups by sector in Germany (Fig. 3). Here it can be seen that the AI landscape and applications in Germany reflect the strong automotive and manufacturing sectors (Seitz et al. 2020).

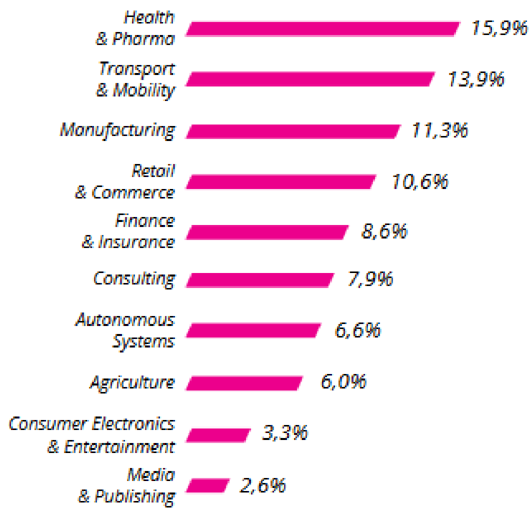


*Figure 3: Distribution of AI start-ups by sector (source: Seitz et al. 2020)*

## 2. AI-Strategy

Because AI offers so many opportunities, decision-makers in business and politics want to promote AI and steer AI development. To this end, fundamental strategies are being developed and, in some cases, published. This section provides an overview.

### 2.1. Global competitive landscape

The USA is the global leader in the field of AI, both in terms of the number of AI players and the sums invested, followed by China and the EU (Righi et al. 2022, Maslej et al. 2023). In 2022, 47.4 billion dollars were invested in AI in the USA, followed by China with 13.4 billion dollars (Maslej et al. 2023). The private sector plays an important role in the USA when it comes to AI. Apart from the large financial resources of the US 'Big Tech companies' (Google (Alphabet), Facebook (Meta), Amazon and Microsoft), the use and processing of their users' data (this is especially true for Meta, Alphabet and Amazon) is a great advantage for the training and development of algorithms, machine learning and the development of artificial neural networks (Annoni et al. 2018).

China is the leader in the number of publications in AI journals, conferences and repositories (Maslej et al. 2023). However, the USA is in the lead when it comes to citations (both for conferences and repositories) (ibid.). The USA and China also have the most transnational publications in the field of AI (ibid.). China's AI landscape is characterised by a large number of new patent applications (Righi et al. 2022). However, Righi et al. (2022) emphasise that lower standards regarding patent quality and recent policies in China, has led to patent filing inflation. Nevertheless, China should still be seen as an important player in the field of AI. Not only because many AI-related patents are still being filed in China, but also because of its prominent role in the ICT manufacturing sector. In addition, AI companies in China have access to enormous amounts of data.

The EU is a leader when it comes to robotics and AI services (Righi et al. 2022). In robotics, this includes the development of autonomous robots and trade in industrial robots. In addition, the EU is experiencing a steady increase in the number of new robotics start-ups. In AI services, this includes infrastructure, platform and software services. In addition, the EU is strong in AI research and development. Nevertheless, the EU has some catching up to do in the field of AI. Furthermore, the UK is a major player in the field of AI, so that 'Brexit' has led to a reduction in the EU's overall strength in the field of AI (ibid.).

## 2.2. The EU’s AI Strategy

The EU's approach to AI aims to build trust, protect fundamental rights and promote industrial capacity and research in the field of AI (EC website, A European approach to artificial intelligence, 2023). In 2018, the EU Commission presented the EU's AI strategy in the communication *Artificial Intelligence for Europe*. The communication emphasises the need for a coordinated approach. The key objectives include strengthening the EU's industrial and technological capabilities in the field of AI, creating an ethical and legal framework for AI and preparing for the socio-economic changes that AI will bring (p. 4, Artificial Intelligence for Europe, COMM (2018) 237 final).

In 2021, the EU Commission then published the ‘AI Package’. This includes the Communication on *Fostering a European approach to AI*, the *Coordinated Plan on Artificial Intelligence* and a *Regulatory framework proposal for AI (AI Act)*. The first communication provides the context for the other two documents. The most interesting of these is the Coordinated Plan on AI.

The 2021 Coordinated Plan on AI is an update to the original 2018 version. For example, the 2018 Coordinated Plan identified the goals of increasing public-private AI partnerships and funding for SMEs, fostering collaboration between AI research centres and, most importantly, **building European data spaces.** Data spaces are seen as a central component in increasing access to data, which is important for AI. The 2021 version then emphasises that investment in AI technologies must be accelerated, that AI strategies and programmes must be implemented in a timely manner and that policy measures for AI must be aligned.

## 2.3. Germany’s AI Strategy

In 2018, the German government adopted its AI strategy. At the centre of the strategy are the goals: "We want to secure Germany's excellence as a centre of research, expand the competitiveness of the German economy and promote the diverse application possibilities of AI in all areas of society in the interests of tangible social progress and in the interests of citizens (p.6)."

The federal government plans to provide around three billion euros for the implementation of the strategy by 2025.

In concrete terms, this includes a number of initiatives. For example, increased support for AI research institutions, the creation of additional professorships in the field of AI or the establishment of a German observatory for AI. In addition, the aim is to further develop the PLS into a platform for AI to enable a space for exchange between politics, business and the scientific community. Support for data spaces is also significant: "We will closely support the European Commission in implementing and updating the initiative to establish the European Data Spaces (AI Strategy 2018, p. 34)." One relevant development - starting in 2020 - as an implementation of the AI strategy is the 'AI Innovation Competition (*KI-Innovationswettbewerb*)' of the German Federal Ministry for Economic Affairs and Climate Action (BMWK). In 2020, the Federal Government published their update of the AI strategy. Here, the Federal Government "takes up current developments in the field of AI and sharpens, strengthens and supplements its measures to promote AI in Germany and Europe (p. 4, AI Strategy Update 2020)".

# 3. Gaia-X

## 3.1. Overview

Gaia-X is a decentralised, federated ecosystem for the sovereign exchange of data and digital services. It is designed in accordance with European values and rules and provides an interoperable infrastructure based on common rules and standards. The Gaia-X *Trust Framework* and the Gaia-X *Policy Rules* define the basis for trust and conformity, as well as semantic interoperability. At the centre of Gaia-X is the creation of an open, transparent and trustworthy ecosystem that enables participants to offer data and digital services while retaining control (sovereignty) over their data. The full potential of Gaia-X will be realised when services can be seamlessly exchanged and orchestrated across data spaces, companies and borders to break down today's data silos, enabling further smart services and creating connected ecosystems. In such an ecosystem of ecosystems, the participants can benefit from each other and fully utilise the value of their data and services.

The Gaia-X framework is based on three conceptual pillars: **Gaia-X Compliance**, **Data Spaces / Federations** and **Data Exchange**. Gaia-X Compliance is defined and measurable by common rules and decentralised services that enable objective and measurable trust (Gaia-X Framework AISBL). This is made possible by the 'Gaia-X Digital Clearing Houses (GXDCH)' and the operation of the 'Compliance Service', 'Registry Service' and 'Notarisation Services' in conjunction with the *Rules* and *Labelling Criteria*. Data Spaces / Federations are interoperable and portable (cross-sector) datasets and services. For Gaia-X compliant Data Exchange, there are rules that define the minimum requirements for transparency, contracts, identities, access and data utilisation.

There are three types of deliverables for each of these pillars: functional specifications, technical specifications and software. The functional specifications include the *Policy Rules and*

*Label Document* (Compliance) and the *Architecture Document* (Data Spaces/Federations and Data Exchange). The technical specification *Trust Framework* covers all three pillars. The technical specification *Federated Catalogue* and the *Identity, Credential and Access Management* fall under Data Spaces/Federations and the *Data Exchange Services* under Data Exchange. As far as the software is concerned, this is developed by an open-source community to create, manage and operate federations and services in order to achieve Gaia-X conformity (Gaia-X Framework AISBL).

When considering Gaia-X in the context of European and German AI strategies, it becomes clear that Gaia-X makes a significant contribution. In addition to the fact that Gaia-X is being built with consideration to EU values and laws (also in relation to AI), by creating data spaces Gaia-X contributes to the development of European data spaces, which are mentioned in the EU AI strategy as one of the key factors for AI.

## 3.2. Enabling AI through Gaia-X

This section describes how the Gaia-X ecosystem can enable and promote AI services. However, it should be noted that Gaia-X should not be seen as a solution to all problems related to AI or even digitalisation. Not all challenges faced by AI can be solved by Gaia-X. However, it does offer solutions to some specific challenges facing the development of AI.

### 3.2.1 Economics / Organisation

#### Trust

A central added value of Gaia-X is the goal of building a trustworthy ecosystem for data sharing. An important feature for creating trust is the Gaia-X *Trust Framework* with the role of 'Trust Anchors'. Trust anchors confirm the identities of the actors and check whether the claims and self-declared statements of the participants are correct. For example, a trust anchor checks the identity of participants and is liable for incorrect verifications. This is done using existing and regulated verification procedures, for example within the framework of eIDAS (Electronic Identification and Trust Services). Trustworthy trust anchors are collectively determined by the Gaia-X AISBL members and can also be removed by them in the event of violations or errors. This means that the other participants can be confident that they know who they are dealing with and can verify this information in real time. It also lets participants know who can be held accountable in the event of non-compliance and, conversely, incentivises participants to adhere to the rules and guidelines set out in Gaia-X. Within the Gaia-X ecosystem, the Gaia-X Clearing House (GXDCH) ensures confidence that participants generally comply with the Gaia-X rules. This acts as a node for checking compliance with the rules and for the participants who become part of the Gaia-X ecosystem. GXDCHs provide clear answers in real time regarding compliance with the minimum requirements for Gaia-X compliance. Based on these answers, all players in the Gaia-X ecosystem are able to better assess the trustworthiness of other players and their offerings, a crucial basis for building a relationship.

Even more specific to the creation of trust in the AI context is the fact that the data and algorithms used in the Gaia-X ecosystem are more transparent and traceable. Figure 4, for example, shows the main model of the service composition. Here, for example, it is possible to trace who provides the service (with a resolvable link to the participant's self-description) through to the details of the resources used. How detailed these descriptions are once the minimum standards have been met is up to the participants, but it is a significant improvement on the status quo and another important measure for building trust. The participants also keep audit trails, which ensure further transparency and traceability.

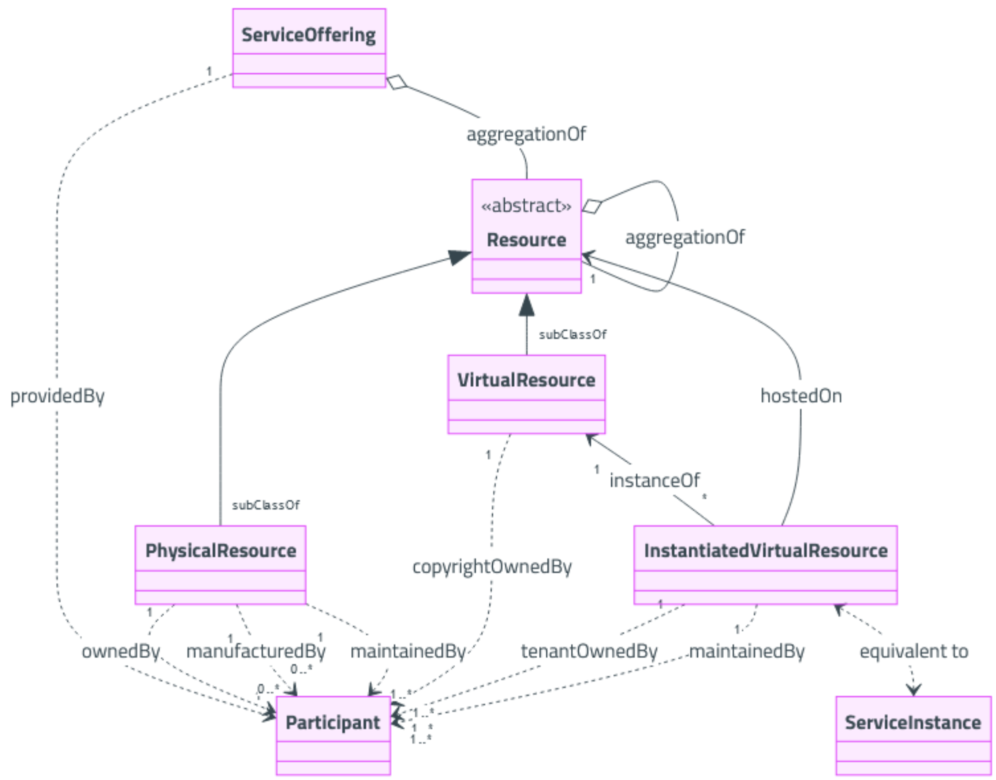


*Figure 4: The main model of service composition (source: Gaia-X Trust Framework)*

## Access to high-quality data

The Gaia-X ecosystem addresses the lack of trust and the reluctance of participants to make their data available for fear of losing control of how, by whom and for what purpose the data can be used. Figure 5 shows, for example, that there is a section with 'policy []' within the general format for all service offerings. Here, a data provider can specify, for example, who may use their data, for what purposes and for how long. Special restrictions that must be implemented due to sectoral regulations can also be made (e.g., export control). The 'dataAccountExport []' is also relevant. This can be used to retrieve your own data at any time. Currently, data can only be recalled proactively (e.g., in the context of the GDPR), otherwise it will not be retrieved. This enables participants to build a legally compliant and traceable data pipeline for data-driven (digital) products and services much more easily and at the same time offer the necessary services on the market.

| Attribute | Card. | Trust Anchor | Comment |
|---|---|---|---|
| `name` | 0..1 | State | A human readable name of the component |
| `providedBy` | 1 | State | a resolvable link to the `participant` self-description providing the service |
| `aggregationOf[]` | 0..* | State | a resolvable link to the `resources` self-description related to the service and that can exist independently of it. |
| `dependsOn[]` | 0..* | State | a resolvable link to the `service offering` self-description related to the service and that can exist independently of it. |
| `termsAndConditions[]` | 1..* | State | a resolvable link to the Terms and Conditions applying to that service. |
| `policy[]` | 1..* | State | a list of `policy` expressed using a DSL (e.g., Rego or ODRL) (access control, throttling, usage, retention, ...) |
| `dataProtectionRegime[]` | 0..* | State | a list of data protection regime from the list available below |
| `dataAccountExport[]` | 1..* | State | list of methods to export data from your user's account out of the service |

*Figure 5: Services offered (source: Gaia-X Trust Framework)*

## Marketplace: consumers and providers

By using catalogue services and the resulting 'Federated Catalogue', participants in the Gaia-X ecosystem can provide and use the resources and services they require with the necessary transparency and information to make informed decisions (for example, who provides the service, what type of data is used, what level of data protection it complies with and so on). The basis for this is the minimum semantic standard defined in the Gaia-X *Trust Framework*, which ensures semantic interoperability of the descriptions.

It also offers market transparency and reach. This allows providers to make AI-related services available to a larger number of potential consumers, as the catalogues can be accessed freely for the most part. Providers who may not have had the resources to be visible to potential consumers, who were previously only active on a few centralised platforms, or who offer a niche AI-related service, now have the opportunity to connect with potential consumers in Europe and beyond on an unprecedented scale. Conversely, consumers can discover and find services they were previously unaware of. Through interoperability and integration within the Gaia-X ecosystem, they can gain access to and combine different resources that potentially cover many steps of the data value chain and open up new business opportunities. For example, a company that has a lot of unstructured data acquires a resource to cleanse the data set, another resource to ensure that the data and subsequent analysis complies with all necessary regulations, and finally a resource to analyse the data and gain new business insights from it. At the same time, the necessary infrastructure can also be rented with the required level of confidence and the price points can be compared on an open market.

This transparency and interoperability also offer participants an additional advantage - especially in the AI context - namely scalability. There is no need to create new contracts, terms and conditions or check compatible formatting or semantics for each new customer, where many of the AI processes can be easily customised and applied much more seamlessly to a larger number of participants. The Gaia-X ecosystem can therefore accelerate the introduction of AI in various sectors. In addition, by breaking down data silos and bringing together different participants from different fields and sectors, new innovations, including new AI applications, can emerge. Together with new orchestration methods - such as compute-to-data, federated learning and federated analytics - it also enables access to data sources that were previously inaccessible to AI service providers.

#### Lack of qualified specialists

Of course, Gaia-X cannot solve the problem that many companies face: a shortage of AI- and IT-skilled labour. But it can significantly minimise the problems it leads to by greatly increasing efficiency. In the Gaia-X ecosystem, for example, a company can purchase on-demand resources that it does not have itself. As shown in the example above, this can range from resources for cleansing unstructured data to access to analysis services for its own data and infrastructural resources such as data storage. This means that even a small company that may not yet be digitally mature and simply has a lot of data can use the Gaia-X ecosystem and gain the benefits of the digital economy. In the specific case of AI, this also means that a whole range of participants who previously may not have wanted to provide data or were unable to assess the value of their data suddenly have much more incentive to make it available for AI systems. Conversely, they could also benefit from the advantages of AI and the insights gained from their own data. In the long term, these improved market conditions will also support investment in skilled labour.

### 3.2.2 Technology

#### Interoperable infrastructure

Interoperability is a central feature of the Gaia-X ecosystem. Many aspects of the ecosystem are based on already existing and established standards (e.g., from W3C) or technical components (International Data Spaces, Eclipse Cross Federation Services, Ocean Protocol, Eclipse Data Space Components, FIWARE, etc.) that use open-source software and are overall compatible with other data exchange infrastructures. This means that participants can integrate and utilise the Gaia-X infrastructure more quickly and seamlessly. Furthermore, interoperability within the Gaia-X ecosystem is a major advantage for AI systems. AI systems often require data from different sources, traditionally with the problem that data from different sources and sectors have different formatting, semantics, etc. In the Gaia-X ecosystem, however, there is interoperability, for example semantic interoperability, so that AI system developers can seamlessly access data from different sectors and sources and references to schemas and ontologies that support the selection and transformation of required data. Approaches to technical interoperability are also being developed on the basis of semantic interoperability using protocols, interfaces and translation tools.

### Data quality

Data offerings do not have to be of particularly high quality to be authorised for use in the Gaia-X ecosystems. This would already represent a barrier for certain participants. However, participants providing data services can provide information on the format, quality, origin, timeliness and maintenance of their data. Further details in the federated catalogue and the self-descriptions of the resources (in this case the data) help interested parties to assess and check the quality of the data. This is supplemented by the possibility of recording digital certifications for data quality, carrying out automated checking processes and making comparisons. In the case of AI, these factors provide participants who want to use the data to train their AI algorithms with the transparency to see the context of the data. As the quality of data from different providers is more transparent and easier to compare (when comparing the different credentials, etc.), this naturally incentivises the provision of higher quality data. Most importantly, the transparency mechanisms and the use of common standards within the Gaia-X ecosystem contribute to the consistency, reliability and accuracy of the data used to train AI models.

### High Performance Computing (HPC)

Gaia-X already enables the provision of infrastructure services (from the edge to the cloud) for sophisticated AI applications and aims to increasingly integrate high-performance computing into its ecosystem. The Gauss Centre for Supercomputing (GCS), which includes the Supercomputing Centre Stuttgart, the Jülich Supercomputing Centre and the Leibniz Supercomputing Centre, became a member of the Gaia-X Association in 2021 (GCS 2021). In Germany itself, a Gaia-X project is already underway, in which both the Jülich Supercomputing Centre and the Centre for Information Services and High-Performance Computing (ZIH) in Dresden are involved in the development of its AI systems. As the amount of data generated and collected is constantly increasing, the demand for more powerful computers will also grow. There are therefore even plans to offer high performance and quantum computing 'as a service' within the Gaia-X ecosystem. This would naturally increase the number of potential customers and users. Overall, the integration of HPC into the Gaia-X ecosystem not only simplifies the use of HPC by AI developers, but also increases the number of potential customers and, conversely, benefits a larger number of organisations developing AI systems. This could help to make transparent how great the demand for such high-performance computers actually is, making investments in the expansion of the infrastructure more tangible and profitable.

### 3.2.3 Regulation

#### AI Act

The Gaia-X ecosystem offers many features that facilitate compliance with the proposed AI Act. In particular, those whose AI systems are categorised as 'high risk' must meet a number of requirements, including transparency, traceability and the use of high-quality data. The Federated Catalogue, for example, allows participants working in the field of AI to view and trace the details of the datasets provided, such as what type of data it is, who provided it and so on. In addition, the Gaia-X ecosystem allows participants to check and ensure that the data is of sufficiently high quality. However, as the AI Act has not yet been finalised and entered into force, it is still too early to provide a complete overview of the extent to which the Gaia-X rules harmonise with the AI Act.

#### General Data Protection Regulation (GDPR)

The Gaia-X ecosystem is designed to be compliant with European regulations. As the central point of contact, the Gaia-X Digital Clearing House (GXDCH) makes it possible to check both compliance with the Gaia-X rules and compliance with legal regulations, such as the GDPR, in an automated manner.

The various label levels, which describe the degree of compliance of a service, are also relevant (Fig. 6). All services must at least comply with the *Gaia-X Policy Rules* and the *Architecture* documents, including the data protection requirements of the GDPR. Depending on whether participants want additional guarantees or work with particularly sensitive data and want to protect their data from non-European regulations (such as the US Cloud Act), they can ensure that the chosen service is based in Europe.

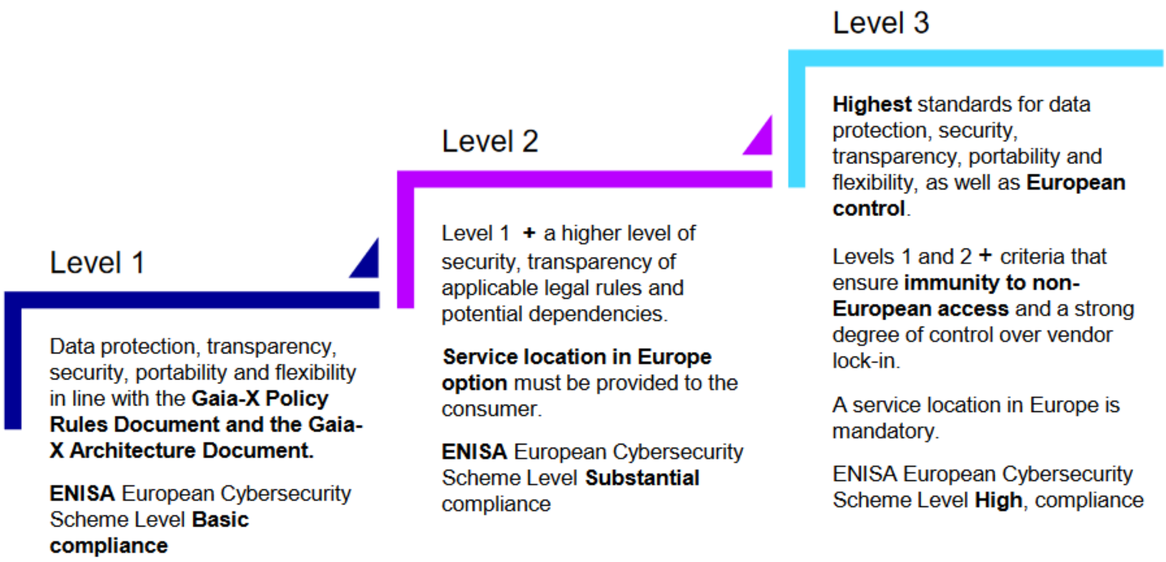


*Figure 6: Gaia-X Levels (source: Bonfiglio 2022)*

For AI, it is particularly relevant that the Gaia-X ecosystem includes **compute-to-edge** applications and **federated learning**. Here, AI algorithms can be trained locally, with the data itself never leaving the data provider's servers. This not only allows those providing the data to retain full control over the data, but also increases data security and ensures compliance with the GDPR.

# 4. Gaia-X AI case studies

Three projects were selected here as examples from many Gaia-X projects dealing with AI. EuProGigant (Industry 4.0) and Gaia-X 4 AI (Mobility) were selected due to the importance of these sectors for the German economy (as shown in Figs. 2 and 3). OpenGPT-X (large language models) was selected because large language models are responsible for much of the current enthusiasm for AI.

## 4.1. Industry 4.0 (EuProGigant)

The '*Europäische Produktionsgiganet*' EuProGigant is one of currently ten Gaia-X lighthouse projects and deals with the intelligent and sovereign use of data for manufacturing. The aim is to establish a digitally networked manufacturing ecosystem across locations. This ecosystem connects companies and research institutions in the manufacturing industry at all levels of the value chain and, in line with the Gaia-X approach, also focuses on the topic of edge computing in addition to the cloud services (see Figure 7). Figure 8 shows a general overview of the EuProGigant ecosystem.

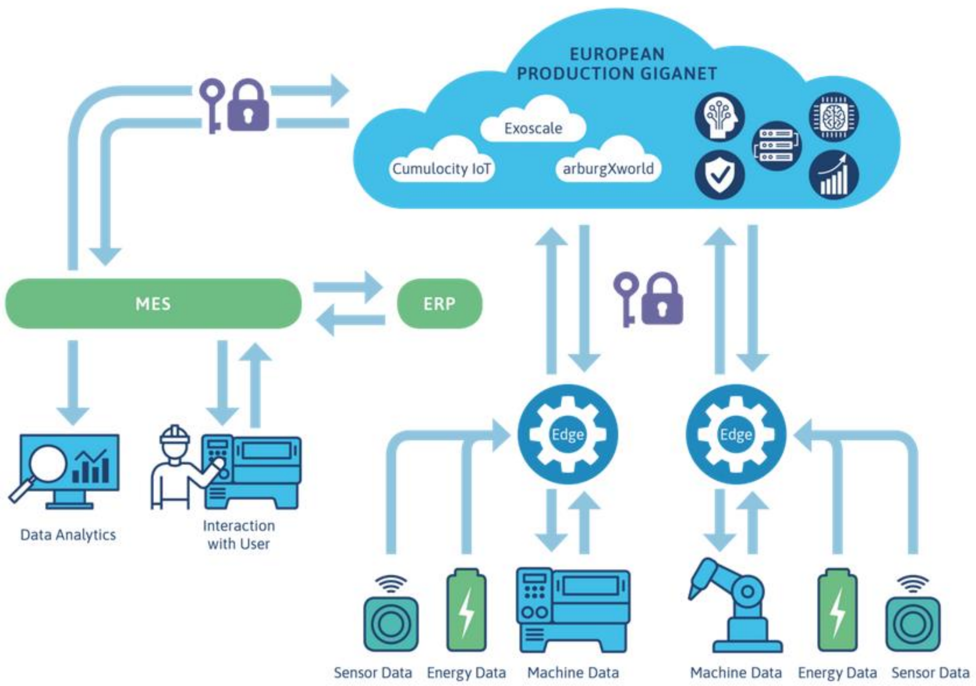


*Figure 7: Vertical integration - cross-case project structure as the universal backbone of the project (source: EuProGigant)*

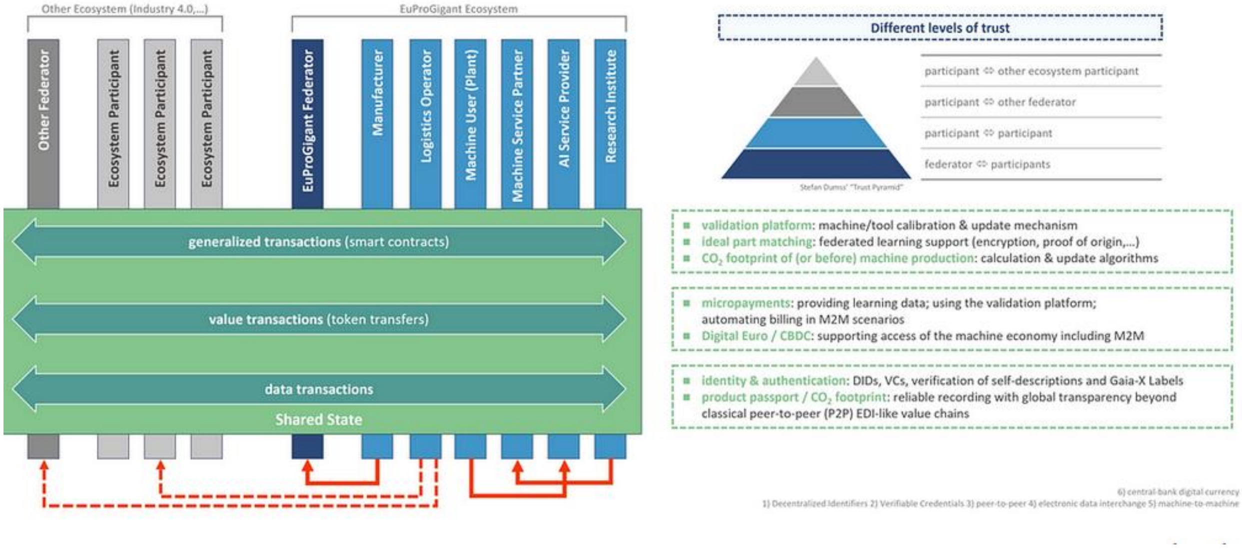


*Figure 8: EuProGigant Ecosystem: Business and Service Modelling — Distributed Ledger Technology (DLT) Potential Use Cases at Medium Trust Level (source: Strnadl, Workshop Gaia-X Lighthouse Projects, Munich, November 10, 2022)*

As part of a German-Austrian consortium led by the Pilot Factory Industry 4.0 at the TU Vienna and the Institute for Production Management, Technology and Machine Tools (PTW) at the TU Darmstadt, the ecosystem is being set up, where through self-orchestration a Governance between participants is envisioned.

Concrete application scenarios are currently being considered in four use cases that address important problems in the manufacturing industry and in which the joint utilisation of data is of crucial importance:

- $CO_2$- footprint in the product development process - provision of $CO_2$-equivalent data in the product design phase to influence the carbon footprint in product manufacturing
- Validation platform - cross-company cooperation to create a database of machines and test beds for effective condition monitoring with the aim of collaborative use of hardware resources, for example in component testing and machine utilisation
- Ideal component matching: optimised, data-based compilation of assembly components
- Mobile processing machine: Processing and utilisation of large amounts of data in the mobile use of machines

Such use cases are used to analyse current challenges in manufacturing. These include the lack of flexibility due to extensive automation and cross-border supply chains with low stock levels, which become particularly evident when there is a sudden drop in demand or bottlenecks in the supply of primary products. EuProGigant makes it possible to prevent and circumvent such potential problem by increasing the availability of data and services and thus promoting the development and use of AI.

This can be illustrated using the 'validation platform' use case as an example: digital ecosystems allow different companies to be networked in such a way that they can share their expertise with each other without jeopardising their intellectual property. This is demonstrated using an AI service for monitoring the condition of milling tools based on the machine data of a manufacturing centre.

So far, predictive maintenance has only been possible in a limited number of cases. The prediction of maintenance requirements, which is generally based on AI, requires large amounts of data and AI development skills. To implement this, a company must, for example, have a correspondingly large number of systems of the same type in operation in order to generate a sufficient data basis or have a specialised department that develops and uses AI models. However, only a relatively small proportion of companies fulfil these requirements. Gaia-X projects such as EuProGigant rely on the exchange of data and services as an alternative. Especially SMEs can offer their data in the ecosystem and thus create a sufficient common data basis. In turn, software providers can use this basis to create the algorithm and develop AI models. Via the ecosystem, these providers can ultimately offer their services back to the manufacturing companies for use and, if necessary, even transfer them to the individual production systems used.

This interaction is made possible in the application example by the structure of the validation platform described above, which is based on the Gaia-X reference architecture using the corresponding federation services Pontus-X and, in future, Eclipse Cross Federation Services Components (XFSC). In this way, the possibilities for secure identification, secure data transfer and compliance provided by Gaia-X can be used. Gaia-X, the XFSC, and the Pontus-X ecosystem (see Figure 10) form the framework in the case of EuProGigant, for realising data value chains in an ecosystem with various providers (including small and medium-sized enterprises) which were previously primarily the preserve of large companies.

### 4.1. Mobility (Gaia-X 4 Future Mobility and Gaia-X 4 AI)

The Gaia-X 4 Future Mobility project family is part of the mobility domain. Gaia-X 4 Future Mobility currently includes six projects funded by the BMWK: Gaia-X 4 AI, Gaia-X 4 AMS, Gaia-X 4 ROMS, Gaia-X 4 PLC-AAD, Gaia-X 4 moveID and Gaia-X 4 AGEDA. The focus of all projects is on the Gaia-X-based implementation of future mobility applications. Due to the product proximity of the applications, data-based networking with manufacturers, suppliers, service providers and users is particularly important. The focus here is on the Gaia-X 4 AI project.

"The world of technical systems in the mobility sector is highly dynamic. The level of complexity is now reaching or exceeding the limits of feasibility of established, engineering-based methods and tools. New innovative methods are therefore being sought and established (p.3, Knake-Langhorst et al. 2021)". AI is an important key technology in the development of complex technical systems - this applies in particular to the field of mobility. The prerequisite for the successful application of AI is the broad availability of adequate data, services and IT resources. Gaia-X paves the way for the establishment of a digital ecosystem. The combination of AI and Gaia-X in one project makes it possible to make application-related contributions to the development of Gaia-X by investigating its use in automated and connected driving (AVF) and industrial manufacturing use cases. The objectives in the industrial application area are the homogenisation of production quality and the design and development of continuously optimisable and system-transferable AI algorithms. The AVF use cases focus on the areas of condition and cyber security monitoring as well as virtual and simulation-based testing. AI-based inspection solutions and quality forecasts are also the focussed on in production.

By linking these usually separate fields of application, concepts and designs for a closed data cycle can be developed across the entire product life cycle, allowing the potential of a shared data and service ecosystem to be maximised. Integrated databases, standardised data interfaces and shared data services are being developed as part of the project. The coupling with other domain-specific data spaces also enables the utilisation of relevant data assets for applications beyond the focused areas of work.

The opportunities arising from the project framework are reflected well in two 'minimal examples' that are being developed and worked on in the project. The project understands the term 'minimal example' to mean pilot applications on the basis of which cross-structural work and initial practical experience in dealing with Gaia-X technologies are made possible at an early stage and at a low threshold in the project. The CARLA minimal example includes, for example, the cloud-based connection and utilisation of the simulation framework of the same name. Figure 9 shows the basic system architecture. The challenge here lies in linking large amounts of data with complex software services for different stakeholders. The resulting services can then be used in the development of AVF use cases. While the findings from this work are already valuable for the Gaia-X 4 AI project, the results of the work can be used as a basis for the development and targeted testing of AI algorithms - in Gaia-X 4 AI itself as well as in the context of the affiliated projects.

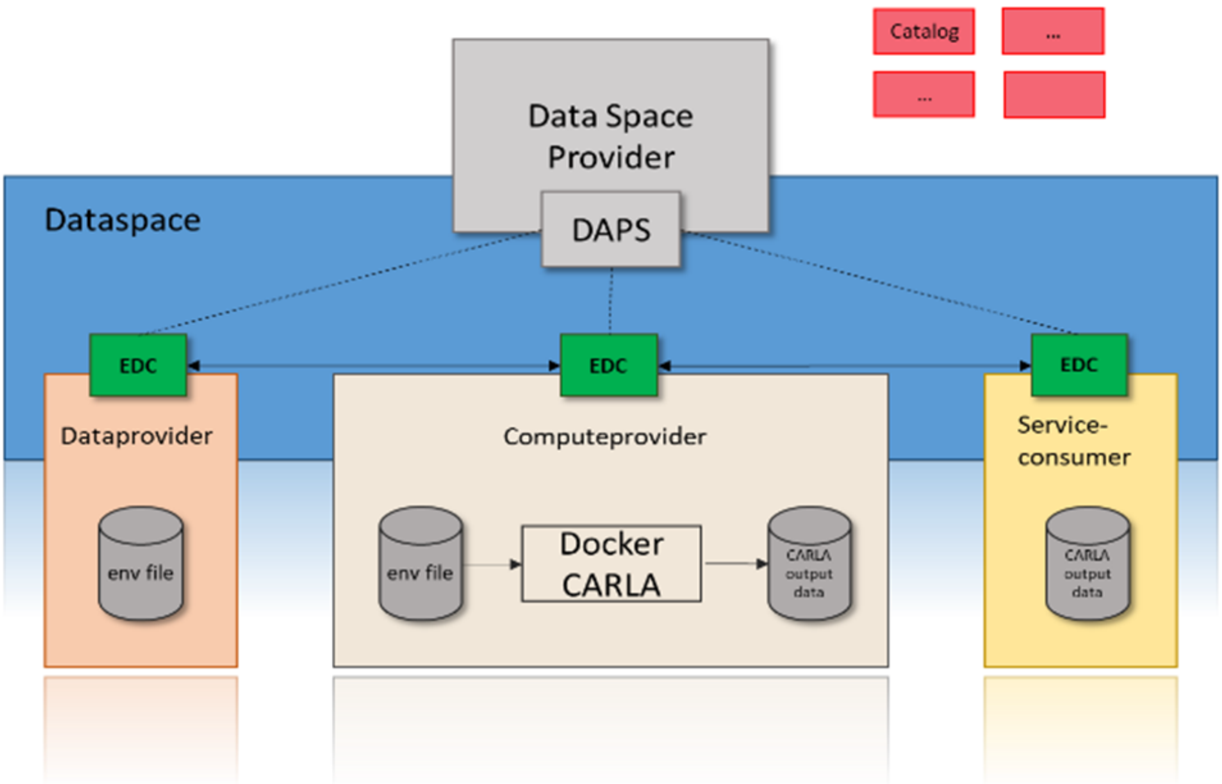


*Figure 9: CARLA-Use Case in the Project Gaia-X 4 KI (source: Gaia-X 4 KI)*

The Minimal Example AI Training Pipeline creates a cloud-based process chain for training AI functions. It is therefore a very good example of researching the requirements for an open data and service infrastructure. Once completed, this service can be used across applications and domains.

The two examples show how the connections described above unlock synergies and potential in the project and enable overarching relationships between AI and Gaia-X.

Another unique selling point of the Gaia-X lighthouse project family Gaia-X 4 Future Mobility is that all technological ecosystems are already represented here and are used to offer and orchestrate AI services, for example the Eclipse Cross Federation Service Components, Ocean Protocol, the Eclipse Dataspace Components and various SSI infrastructures to realise Gaia-X-compliant and open identity ecosystem services.

In this context, the same ecosystem services (catalogue services, contract services, payment services, logging) are used as those for EuProGigant, so that both ecosystems can also exchange and collaborate on an ad hoc basis.

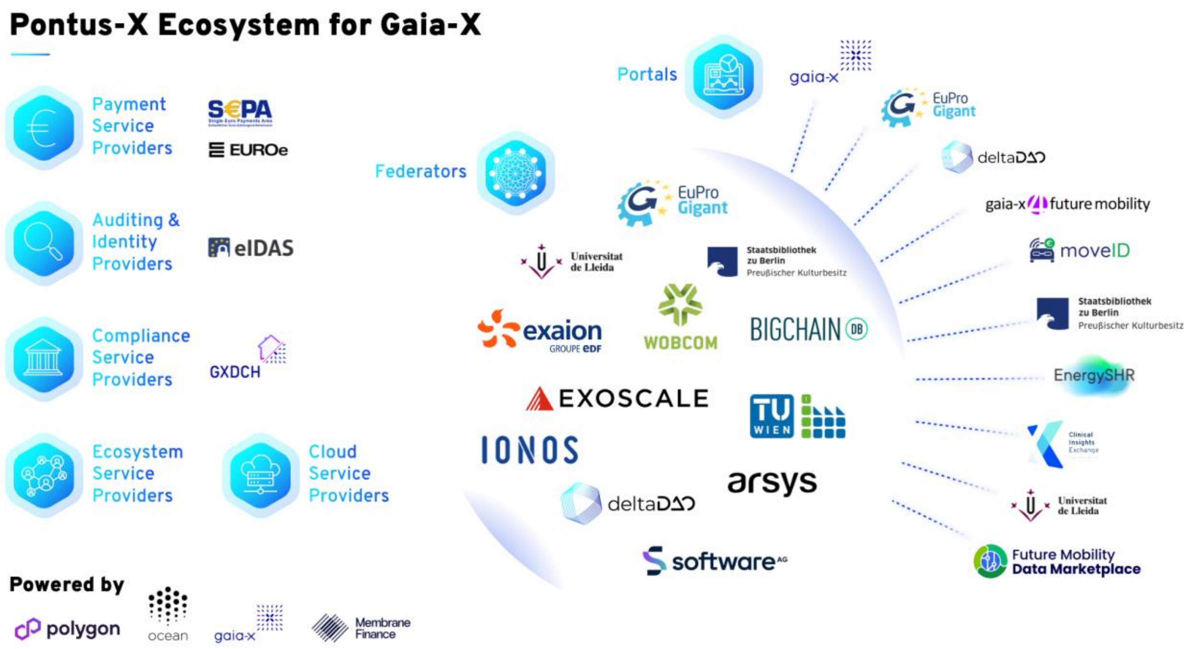


*Figure 10: Pontus-X-Ecosystem (source: deltaDAO AG)*

### 4.2. Large Language Models (OpenGPT-X)

Large AI language models have so far mainly been developed by large corporations in the USA and China. They are usually only available on the open market to a limited extent; they cannot be customised and are usually only available in English or Chinese. Services based on these models, such as ‘ChatGPT’, usually store and process their data outside Europe. This means that sensitive or personal data often cannot be processed in a legally secure manner. The resulting lack of usability of large AI language models for the German and European market represents a significant competitive disadvantage for all sectors. In the manufacturing sector in

particular, the technology could boost the efficiency of production processes to a much higher level.
The aim of the OpenGPT-X project is to develop large, multilingual AI language models at the European level in order to strengthen both digital sovereignty and Europe's long-term innovation and competitiveness in this sector. The project is a consortium of the Gaia-X funding competition 'Innovative and practical applications and data spaces in the digital ecosystem Gaia-X'. Through the integration into the open, interoperable Gaia-X ecosystem, data storage and processing are done in accordance with European data protection and security standards. This is intended to offer companies the best possible framework conditions for utilising sensitive or personal data. The training itself can take place via distributed infrastructures in European data centres, with other projects in the Gaia-X environment ensuring the necessary compatibility and interoperability of powerful cloud services. Thanks to open interfaces and a Gaia-X-compliant data space, both businesses and the public sector can use the models developed by OpenGPT-X as the basis for innovative language services in a legally compliant manner. The technical structure enables fast and affordable adaptation and scalability. This means that services in different languages or with customised industry vocabulary can be used modularly without significant additional effort. Only by developing a self-sufficient, German-European language model and building up in-house expertise in this area is it possible to deal with the known problems of large AI language models in the first place: the possibility of customisability strengthens control over the models, while integration into Gaia-X as a publicly accessible open-source language model promotes transparency and traceability.

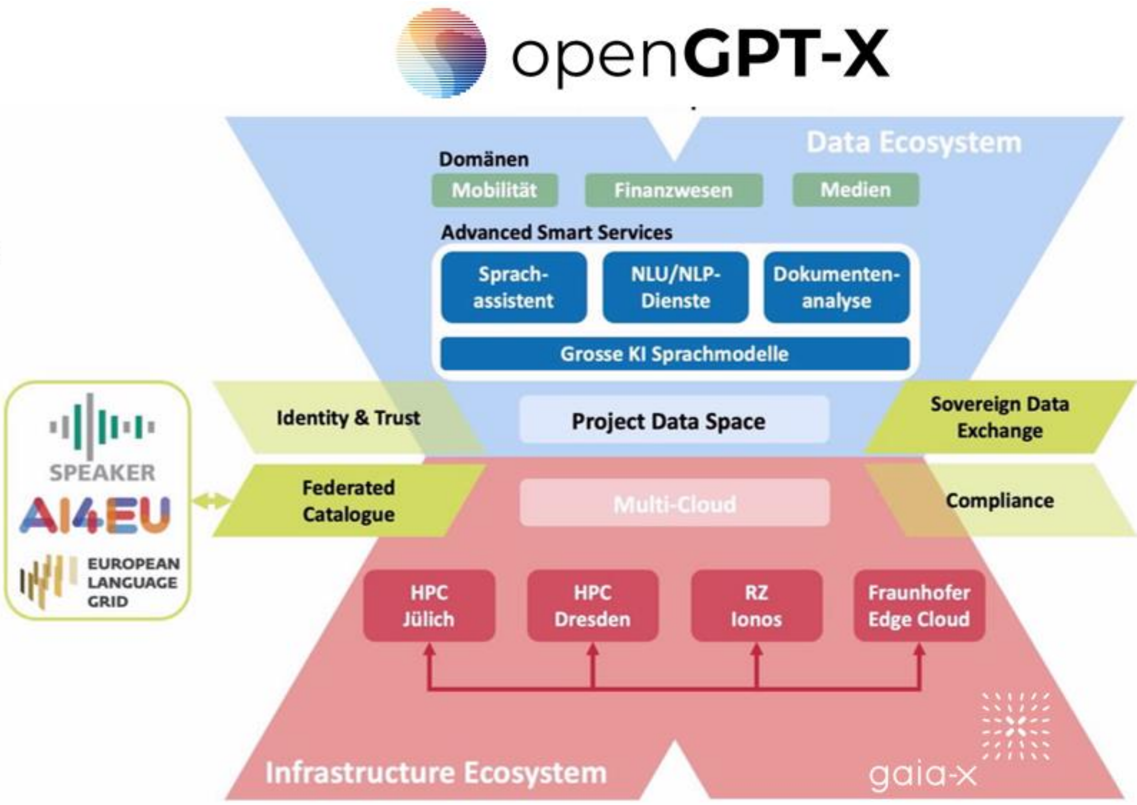

*Figure 11: Infrastructure of the OpenGPT-X project (source: OpenGPT-X).*

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